Tariff-based Analysis of Commercial Building Electricity Prices *

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Abstract

This paper presents the results of a survey and analysis of electricity tariffs and marginal electricity prices for commercial buildings. The tariff data come from a survey of 90 utilities and 250 tariffs for non-residential customers collected in 2004 as part of the Tariff Analysis Project at LBNL [2]. The goals of this analysis are to provide useful summary data on the marginal electricity prices commercial customers actually see, and insight into the factors that are most important in determining prices under different circumstances. We provide a new, empirically-based definition of several marginal prices: the effective marginal price, and energy-only and demand-only prices, and derive a simple formula that expresses the dependence of the effective marginal price on the marginal load factor. The latter is a variable that can be used to characterize the load impacts of a particular end-use or efficiency measure. We calculate all these prices for eleven regions within the continental U.S. The methodology developed here can be adapted to any particular customer or utility sub-sample that may be of interest.

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Symbol	Definition
u	Utility index
R	Region index
P	Ownership type index
$\mathcal{U}_{P,R}$	Set of all utilities in region R of ownership type P (from EIA data)
$\mathcal{U}_R$	Set of all utilities in region R (from EIA data)
$\mathcal{S}_{P,R}$	Set of sample utilities in region R of ownership type P
$\mathcal{S}_R$	Set of all sample utilities in region R
$M(P,R)$	Number of customers served by ownership type in region R
$N(R)$	Total number of customers in region R
$q(R)$	Weighted average revenues divided by sales for utilities in R (from EIA data)
σ_q	Standard deviation of q
$W(u)$	Sample weight for utility u
b	Building or customer index
$x(b)$	Sample weight for customer b
$w(b,u)$	Sample weight for the account defined by customer b and utility u
E	Billing period energy consumption
D	Billing period peak demand
N_h	Number of hours in the billing period
B	Billing period total bill in dollars
L	Billing period load factor
$p_{av}(b,u)$	Average electricity price for account (b,u)
$p_{av}(b)$	Average electricity price for customer b
$P_{av}(R)$	Average electricity price for all customers in region R
ΔE	Change to billing period energy consumption
ΔD	Change to billing period peak demand
ΔB	Change to billing period total bill in dollars
Π	Effective marginal price
Π_E	Marginal energy price in ¢per kwh
Π_D	Marginal demand price in $ per kw
$\tilde{\Pi}_D$	Re-scaled marginal demand price in ¢per kwh
λ	Marginal load factor

1 Introduction

In an analysis of the value of energy-efficiency measures, the price paid at the margin for electricity is one of the most important determinants of overall cost-effectiveness. To successfully encourage customers to invest in such measures, it's essential to provide accurate information about potential electricity cost savings, and the conditions under which these savings will occur. Ideally, this information should be based on real tariffs used by utilities. For the large majority of utilities, tariff data is public and is often freely available over the web, but the complexity and diversity of tariff structures presents a considerable barrier to using them in analysis. The purpose of the *Tariff Analysis Project* (TAP) [2] is to develop the tools necessary to record, manage and use this data effectively. The TAP database is built around a statistically representative sample of 90 electric utilities, for which the default residential and general service tariffs were collected. In this paper, we use this information to provide a comprehensive analysis of commercial building electricity prices in the U.S., with a focus on how these prices vary at the margin under different circumstances.

A tariff is a set of rules that define how to calculate a customer bill from information about their energy use. For most non-residential tariffs, this information consists of monthly energy consumption and demand, *i.e.* the tariff specifies the bill as a function of these two parameters. From this function, a variety of prices can be defined. Our primary interest in this paper is what we call the *effective marginal price*. This is defined as the change in the dollar amount of the customer bill divided by the change in energy consumption, given some alteration to the customer's baseline energy use. This definition includes demand charges and/or the effect of changes to the load shape if the tariff is time-of-use. It's an empirical concept, intended to reflect the price a customer would see after implementing some efficiency or other measure that affects their monthly load *shape* as well as total energy use.

Because the customer bill is a function of the customer baseline energy consumption (E) and demand (D), the marginal price will also be a function of these two parameters. This means that two customers on the same tariff may see different marginal prices, in some cases very different. Because the effective marginal price accounts for changes in the load shape, it will also depend on the change to energy consumption (ΔE) and the change to demand (ΔD). As we will show, the dependence of the effective marginal price on ΔE and ΔD can be expressed as a simple function of the *marginal load factor*. This allows us to define, for any given tariff or weighted sum of tariffs, the effective marginal price appropriate to changes to a particular end-use, whether it has the characteristics of a base load (such as refrigeration), an average load (such as lighting) or a peaking load (such as air-conditioning).

In this paper we present results on prices for commercial buildings. The analysis requires both tariff data and bill input data (E and D) for a representative sample of customers. Here we use the electricity bill survey data from CBECS 1992 and 1995 [3, 4]. The tariff data comes from a survey carried out in 2004 [1]. A number of general conclusions can be reached: customers with large monthly energy consumption do not necessarily have small marginal prices; prices are more sensitive to customer load factor than to customer size; complex rate structures are widespread and can lead to a significant difference between the average and marginal price for a given customer; correlations between customer type, customer size, and energy use patterns can lead to important variations in the effective marginal price across different classes of customers.

1.1 Background

Our work on tariffs and marginal prices was initially undertaken as part of the U.S. Department of Energy (DOE) efficiency standards rulemakings for air-conditioning [14] and for distribution transformers [15]. Until recently, the DOE's Appliance Standards Program based its analysis of consumer bill savings on average energy prices. This practice changed in 1998 when the Advisory Committee on Appliance Energy Efficiency Standards delivered recommendations to DOE advocating, among other things, the use of marginal energy prices [12]. The first study in this context used utility bill data (monthly consumption and expenditures) to estimate prices for the residential sector, and a limited tariff survey for the non-residential sector [13]. These analyses were applied to the evaluation of standards for several residential and commercial products, including residential central air conditioning (AC). The electricity prices developed for residential AC were criticized by a number of stakeholders, who argued that retail rates do not accurately reflect the additional cost of serving peaky loads, and consequently that efficiency measures that reduce peak demand as well as energy consumption are under-valued [6, 8, 11]. Recommendations were made to DOE to develop improved estimates of marginal prices to account for these factors. While it is clear that the cost of serving peaky loads is higher than the average cost per-kWh, the question of how much higher and under what conditions cannot be answered without considerable attention to detail. This implies accounting for, at the least, real utility pricing schemes including block rates, time-of-use, demand charges and so-called hours charges. The TAP database incorporates all these features in a standardized format, which makes direct calculation of bills or prices relatively easy, and so frees up analytical resources for use in studying other factors that affect pricing.

[1] All prices are expressed in 2006 dollars to be consistent with the most recent EIA data.

1.2 Outline

The rest of this paper is organized as follows: In Section 2 we discuss the utility sample and present some quantitative measures of how representative it is of the national population. We also enumerate the general characteristics of electricity tariffs. The tariff database structure and related topics are discussed in a separate report [2]. In Section 3 we describe our analysis of customer data taken from the Commercial Building Energy Consumption Surveys (CBECS) of 1992 and 1995. The CBECS data is used to characterize the general population of commercial customers. In Section 4 we present our calculation of electricity prices for this population. For this analysis, the sample utilities are grouped into 11 regions, and weighted average prices are calculated for each. Section 4 also presents our formula for expressing the effective marginal price as a function of the marginal load factor. Our conclusions are presented in Section 5. Additional technical details on the processing of CBECS data are given in Appendix A, and Appendix B provides a list of the utilities used for this analysis.

2 The Utility Sample

The utility sample is designed to reflect the diversity in any industry characteristics that may affect electricity prices, such as location, ownership type, and company size. EIA Form 861 data [5] were used to develop an overview of the industry and to select the set of sample utilities. The data include total dollar revenues, sales in kilowatt hours (kWh) and consumer counts for all the utilities that provide service to final consumers. Ownership type can affect management style, finance costs and other aspects of company practice that impact the way customers are billed. Regional variation implicitly includes climate, demographics and historic regulatory and market arrangements, and is also an important factor influencing price. The utility sample incorporates a level of regional disaggregation sufficient to distinguish both climate and demographic variation. The sample regions are defined by the intersection of the nine census divisions with the nine climate regions defined by the National Climactic Data Center [10]. Different market structures were accounted for by separating out Texas, Florida, New York, California, and the PJM area. The result is a set of 17 subdivisions for the continental United States, as illustrated in figure 1. Note that the utility sample contains data for Alaska and Hawaii, but as these states are not covered in the CBECS surveys, they are not included in this analysis.

The existing TAP tariff sample is valid at the level of the regions defined in figure 1, but for any particular analysis the appropriate level of regional detail also depends on the customer data. Because the CBECS survey data don't include detailed location information, we have aggregated the regions of figure 1 to a smaller set of eleven regions. For each building, CBECS provides the census division and assignment to one of five climate zones. In the eastern and central part of the U.S. the census divisions are small enough to be used as regions in themselves. In the west, given the size and climactic diversity of the Mountain and Pacific census divisions, further subdivision is needed. The Mountain region is divided into regions 8.1 (MT, ID and WY) and 8.2 (NV, UT, CO, AZ and NM), and the Pacific region is divided into 9.1 (WA and OR) and 9.2 (CA). [2]

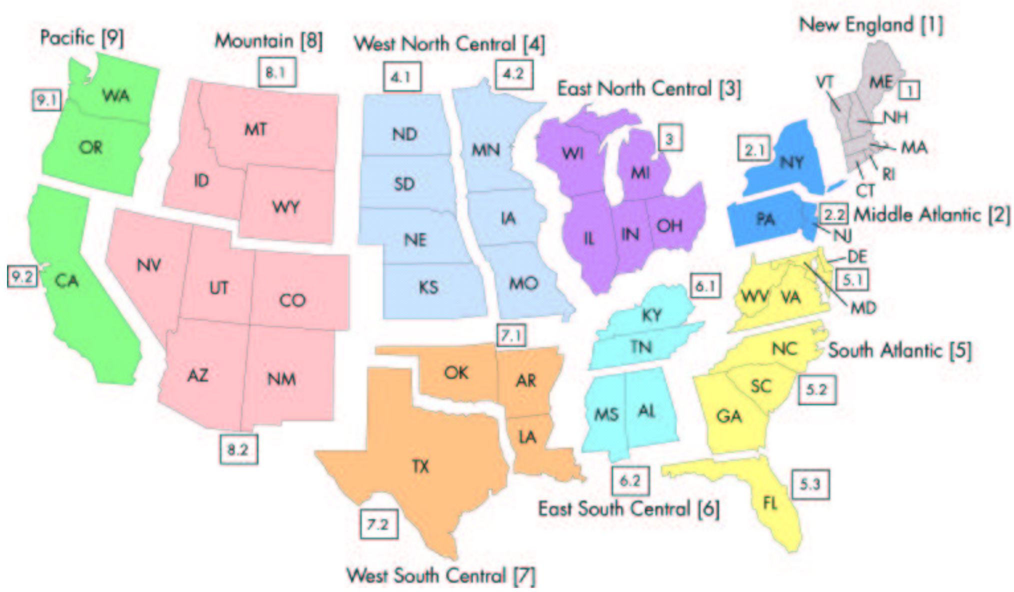

Figure 1: Regions used to develop the utility sample. Census division is indicated by the first digit in the numeric code.

A complete list of the sample utilities is given in Appendix B. Four criteria were used to guide the choice of sample utilities:

- The sample should cover as many customers as possible.
- The regional distribution of customers within the sample should reflect the distribution of population across the country.

[2] Subdivision 8.1 corresponds to CBECS climate zone 1, and subdivision 8.2 to all other climate zones. Subdivision 9.1 corresponds to CBECS climate zones 1, 2 and 3, while subdivision 9.2 includes climate zones 4 and 5.

	Number of Companies		Percent of Companies	
% C&I Customers	Private	Public	Private	Public
20%	6	21	1.1 %	0.7 %
40%	18	101	3.4 %	5.6 %
60%	43	285	8.1 %	10.0 %
80%	82	675	15.4 %	23.7 %
100%	531	2844	100.0 %	100.0 %

Table 1: Number of companies serving a given percentage of C&I customers (based on [5]).

- The sample should reflect the proportion of customers served by private *vs.* public companies. Here we define private as investor-owned utilities and power marketers, and public as municipal, cooperative, county, state or federal utilities.
- For practical purposes, all the utilities chosen for the sample provide service to residential, commercial and industrial customers.

The EIA data show that the utility industry is highly concentrated, as indicated in Table 1. The table is based on the cumulative commercial and industrial (C&I) consumer count for companies ordered from largest to smallest. The columns show the number or percentage of companies that serve each fifth of the total C&I population for public and private companies (public here only includes municipals and cooperatives). In percentage terms the degree of concentration in the two sectors is comparable, but in absolute terms the the number of publicly-owned companies is several times larger than privately-owned. For this reason, our coverage of public companies is less complete than for private companies. Below we explain how the utility weights are defined to ensure that this does not introduce a bias into the regional weighted-averages.

2.1 Tariff Sample Characteristics

The sample characteristics are used to indicate the degree to which the set of utilities in TAP is representative of the full population. Here we use customer counts and average prices estimated from EIA data by region. Of the ninety utilities in the sample, 44 are privately-owned and 46 publicly-owned. The sample companies serve 47% of all C&I customers in the United States. For private companies, the sample covers 58% of all C&I customers, and 14.5% of these customers for public companies. Relative proportions by region are shown in Table 2. This Table also includes a region weight, based on the fraction of total population living in that area, defined below in equation (11).

Region Code	Region Name	Region Weight	All Private	All Public	Sample Private	Sample Public
1	New England	0.048	88 %	12 %	99 %	1 %
2	Mid-Atlantic	0.137	91 %	9 %	90 %	10 %
3	East North Central	0.157	87 %	13 %	97 %	3 %
4	West North Central	0.067	56 %	44 %	90 %	10 %
5	South Atlantic	0.191	73 %	27 %	93 %	7 %
6	East South Central	0.060	38 %	62 %	79 %	21 %
7	West South Central	0.114	71 %	29 %	84 %	16 %
8.1	North Mountain	0.010	71 %	29 %	86 %	14 %
8.2	South Mountain	0.059	66 %	34 %	94 %	6 %
9.1	North Pacific	0.034	57 %	43 %	66 %	34 %
9.2	California	0.123	76 %	24 %	94 %	6 %
	National	1.000	72 %	28 %	91 %	9 %

Table 2: Percentage of C&I customers served by privately- *vs.* publicly-owned companies, for all utilities and for the sample.

The ratio of annual revenues to sales indicates the average amount of revenue collected for each kWh sold. This quantity is in fact the consumption-weighted average price over all the utility's customers, which may or may not provide a good estimate of the utility's average customer price. Even if it isn't a good price estimate, it is still useful as an indicator of how prices vary by region and ownership type. We use it here to compare the degree of variability within the sample to that of the full set of utilities.

Before outlining the calculations we introduce some notation. The set of all utilities in the EIA data is denoted by $\mathcal{U}$, while the set of utilities in the sample is denoted by $\mathcal{S}$. Indexing the region by R, $\mathcal{U}_R$ is the set of all EIA utilities serving customers in region R, and $\mathcal{S}_R$ is the set of sample utilities serving region R.

Let u be an index defining the utility, $v(u)$ be the utility annual revenues, $k(u)$ the annual sales in kWh, and $n(u)$ the total number of customers served by the utility. For each region, we compute the customer-weighted average revenues divided by sales as

$$q(R) = \frac{\sum_{u \in \mathcal{U}_R} n(u)[\, v(u)/k(u)\,]}{\sum_{u \in \mathcal{U}_R} n(u)} \tag{1}$$

where the sum is taken over all utilities in region R. We also compute the standard deviation

Region Name	All Avg	All σ	Sample Avg	Sample σ
New England	14.7	2.8	15.4	2.9
Mid-Atlantic	12.1	4.4	13.9	4.5
ENC	6.9	1.0	7.1	0.5
WNC	6.3	1.4	5.6	0.7
S. Atlantic	7.8	2.2	7.7	2.2
ESC	7.0	1.3	6.1	0.6
WSC	9.3	2.5	7.7	1.6
N. Mountain	5.6	1.8	4.1	0.8
S. Mountain	7.5	1.5	7.7	0.9
N. Pacific	6.2	1.4	5.5	0.4
California	12.6	1.8	13.3	1.1
National	9.1	1.6	9.2	1.7

Table 3: EIA-based average revenues by sales (in ¢/kWh) for all utilities and for the sample.

in this quantity:

$$\sigma_q(R) = \frac{\sum_{u \in \mathcal{U}_R} n(u)[\, v(u)/k(u) - q(R)\,]^2}{\sum_{u \in \mathcal{U}_R} n(u)} \tag{2}$$

The same quantities can be defined using only the sample utilities:

$$q'(R) = \frac{\sum_{u \in \mathcal{S}_R} n(u)[\, v(u)/k(u)\,]}{\sum_{u \in \mathcal{S}_R} n(u)}, \tag{3}$$

and

$$\sigma'_q(R) = \frac{\sum_{u \in \mathcal{S}_R} n(u)[\, v(u)/k(u) - q'(R)\,]^2}{\sum_{u \in \mathcal{S}_R} n(u)}. \tag{4}$$

The values of q, σ_q, q' and σ'_q for each of the eleven regions are shown in Table 3. The sample numbers tend to be a little higher for the highest price regions, and lower elsewhere, although in both cases the sample averages are well within the range defined by one standard deviation.

2.2 Utility Weights

In order to calculate regionally-averaged prices, each utility in the sample must be assigned a weight. The correct weighting scheme to use depends on the application. Here we define weights based on the number of customers served by each utility relative to the rest of the sample. This scheme includes a factor that maintains the correct proportions of publicly *vs.* privately owned utilities. The weights are defined using data for the C&I market, for the eleven geographic regions defined above, but the method is general and can be applied to any market and regional disaggregation.

As above, we use u to index the utility, and define revenues $v(u)$, sales $k(u)$, and consumer counts $n(u)$. Many utilities sell into multiple states, so in computing the regional sums over utilities, we include only sales to states within the given region. The weights depend on both region R and ownership type, which we index by P. Here we use three categories of ownership: private (investor-owned and power marketer), public (cooperative, municipal and county) and government (state and federal). We have added the government sector separately because our sample includes a couple of large federal projects which would skew the public weightings if they were included in that category. The subset of utilities in the full EIA data set, belonging to region R and of ownership type P is denoted $\mathcal{U}_{P,R}$. Similarly, the subset of sample utilities belonging to region R and of ownership type P is denoted $\mathcal{S}_{P,R}$.

We define the aggregate count of customers in region R served by utilities of ownership type P, for all utilities in the EIA data, as

$$M(P,R) = \sum_{u \in \mathcal{U}_{P,R}} n(u). \tag{5}$$

Summing over ownership types

$$N(R) = \sum_{P} M(P,R) \tag{6}$$

is the total number of customers in region R.

Similarly, for the utilities in the sample the count of customers in region R served by utilities of type P is

$$M'(P,R) = \sum_{u \in \mathcal{S}_{P,R}} n(u), \tag{7}$$

and

$$N'(R) = \sum_{P} M'(P,R) \tag{8}$$

is the total number served by sample utilities in region R.

The weight accorded to a utility is proportional to the number of customers served by that utility relative to the total number in that region. We add a normalization factor that ensures that the total weight of different ownership types is the same in the sample as in the full EIA data set. With this definition, the weight for sample utility u of ownership type P, in region R, is:

$$W(u) = \frac{n(u)}{M'(P,R)} \frac{M(P,R)}{N(R)}. \tag{9}$$

It is easy to show that, for each region

$$\sum_{u \in \mathcal{S}_R} W(u) = 1. \tag{10}$$

This normalization is convenient for calculating regionally-averaged quantities. To convert these to national averages, each region is assigned a weight as follows:

$$W(R) = \frac{N(R)}{\sum_R N(R)}. \tag{11}$$

2.3 General Tariff Characteristics

In our survey we found that most utilities do not use the classifications commercial and industrial for their tariffs. Instead, electricity tariffs are classified as residential or non-residential. Non-residential may be further subdivided according to end-use (*e.g.* outdoor lighting), industry type (agriculture or mining), customer load factor, *etc.* Tariffs also specify the delivery voltage and may include charges based on the capacity of the distribution transformer serving the customer.

In this analysis we focus on default non-residential tariffs that would apply to commercial enterprises. Utilities typically segregate this sector according to customer size. Size is almost always defined by value of the annual peak load, although in a few cases it is defined by the maximum monthly energy consumption. Customers are generally not switched from one tariff to another unless a change in their electricity use persists for several months, although there may be rules that change the pricing structure if the energy use and demand in a given month fall outside the limits specified for that tariff. All utilities define a default service class. Our strategy is to collect all the default tariffs by customer size and market type, so that any customer of a given utility can be assigned to a tariff. We include time-of-use (TOU) tariffs whenever they are mandatory. Where distinctions based on service voltage exist, we use the tariff for secondary service. Many utilities have a number of optional schemes such as interruptible service or real-time pricing, but as we do not have any information on how many customers opt for these schemes, they are not included in the analysis. An overview of the basic features found for the sample is presented in table 4, which shows the number

Feature	No. Utilities	No. Tariffs
Total Sample Size	90	247
Fixed Charges	86	224
Energy Charges	90	244
Energy Blocks	60	105
Demand Charges	82	165
Block-by-demand	34	52
Mandatory TOU	15	28
Seasonal Rates	38	90

Table 4: Summary characteristics of the tariff sample.

of tariffs that have fixed, energy or demand charges, the number of mandatory TOU tariffs, the number with seasonal rates *etc.*

Information on how many customers are on each tariff is generally not available. Some data can be gleaned from the Federal Energy Regulatory Commission Form 1 filings [7], but it is incomplete and does not include information for publicly-owned utilities. Instead, we use the CBECS data to infer the distribution of consumers over tariffs from the monthly loads and the building weights.

2.3.1 Charge types and bill calculations

To calculate a customer electricity bill requires two sets of inputs: the rates as defined by the tariff, and information on the customer energy use. In principle, the precise definition of the customer data needed to compute the bill is part of the tariff document. In practice, the customer data usually consists of the billing demand and the total energy consumption for each billing period. In this paper we define the billing period as one calendar month. The billing demand is the peak demand in the current billing period. The same definitions hold for TOU tariffs, except that the billing demand and energy consumption are computed separately for the peak, off-peak, and shoulder periods as defined by the utility.

Charges are classified as *fixed charges* ($), *energy charges* ($/kWh), and *demand charges* ($/kW). Energy and demand charges are typically applied in blocks. The block limits may be constant, or a function of the energy consumption or billing demand. Block rates with at least one of the block limits defined as a multiple of the demand are sometimes called *hours charges* — in this paper we refer to them as *block-by-demand* charges. Block-by-demand rate structures introduce a dependence of the energy charge on demand which can have a significant impact on the effective marginal price.

An illustrative example is presented in Figure 2. Here, in the first block the rate is 10 ¢/kWh for the first 200 kWh of energy used. In the second block the rate is 6 ¢/kWh for energy consumption up to 100 times the billing demand. The multiplier 100 is a tariff component with units of kWh/kW. The third block rate is 3 ¢/kWh for all subsequent energy use. We consider two cases with the same energy use but different billing demand. In Case 1, the energy consumption is 3200 kWh, the demand is 20 kW, and the width of the second block is 2000 kWh. In Case 2, the energy consumption is 3200 kWh, the demand is 21 kW, and the width of the second block is 2100 kWh. Increasing demand by one kW increases the bill by $3 (because 100 kWh of consumption is shifted from the third to the second block), even though the tariff has no explicit demand charges. Any marginal change that includes some demand effect can thus induce a marginal price that is very different from the rate for the highest energy block.

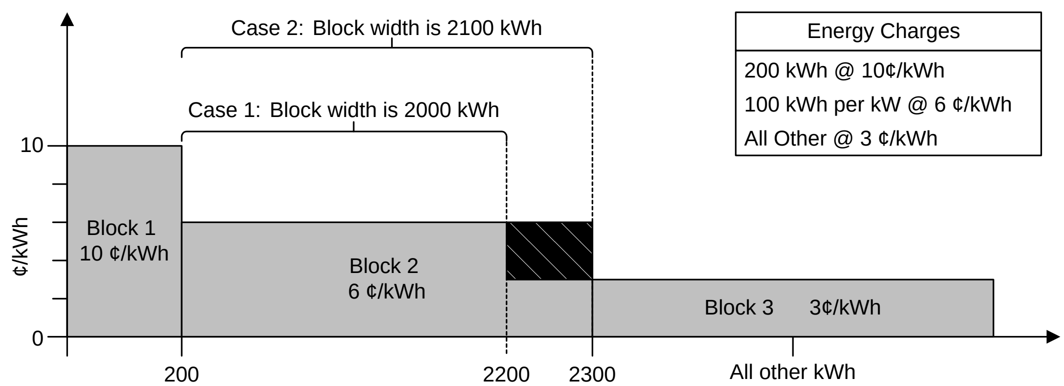

Figure 2: Illustration of the effect of a change in billing demand for a block-by-demand tariff.

The full tariff documents can be quite complex, and may include provisions for charging customers according to criteria that are not fully specified within the document itself, or which depend on customer data that is not easily available. For this reason, some approximations must be made to represent the tariffs within the TAP database. The most significant are as follows:

- Fuel cost recovery adders are neglected unless they are specified as a price per kWh or per kW. Formulae that depend on utility data that are not available with the tariff document are not modeled. This may lead to an underestimation of prices.
- Miscellaneous riders and adders, such as public benefits charges, are included only if the charges are significant (on the order of 0.3 ¢/kWh or larger). Otherwise, the extra

labor required to track down many small adders is not justified. This may lead to an underestimation of prices as most adders are positive, although in some cases riders may specify small price reductions.

- Capacity charges, which are fixed charges determined by the size of the transformer serving the customer, are represented for a given tariff as a single fixed charge. Variations in capacity charges are usually small, and have no effect on the marginal price.

- In a few cases the utility specifies "small" and "large" customer types without providing an explicit definition of these terms. In these cases we define the boundary between small and large as 50 kW demand.

- Ratchets are not modeled in this analysis. A ratchet is a tariff rule that defines the billing demand as the maximum monthly demand over some previous period. A ratchet can have a significant impact on a single customer bill. However, the applications for which TAP is designed usually involve computing customer cost savings over a period of five to fifteen years, based on one year's energy use data. In this case, using a ratchet in that one year would misrepresent the actual billing over the analysis period. For this reason, ratchets have not been included in the current analysis.

- While sales taxes collected by utilities impact the consumer price of electricity, they are not part of the tariff proper, and tax rates are not described in tariff documents. For this reason, they are not included as part of TAP. To get the full price of electricity, the appropriate tax rate should be added to the tariff-based price.

3 Characterization of the Customer Sample

Using a tariff allows direct calculation of the real prices a customer would see under a given set of circumstances. The key point to remember is that, in the non-residential sector, the tariff itself does not completely determine the average or marginal price a customer sees. Customers on the same tariff but having different values of monthly energy consumption E and demand D will see different prices. It follows that marginal prices defined for a sample of commercial customers in general depend on the energy use characteristics of that sample. To develop an estimate of regional average commercial electricity prices, we use billing data [3] from CBECS [3, 4]. The billing data include energy consumption, demand and expenditures for up to 16 billing periods during the survey year. The data are converted to monthly values covering one calendar year. Details on the data processing are presented in Appendix A.

[3]In this analysis, we will use a commercial building as a proxy for a commercial customer.

The surveys provide a statistically complete representation of all commercial buildings in the continental U. S. They have been conducted since 1988 every 3-5 years, but only the 1992 and 1995 surveys include the detailed monthly bill data needed for the tariff-based price analysis. Commercial buildings can be categorized in various ways, for example by size, vintage, primary building activity (restaurant, office) *etc.* While all these factors affect electricity loads , because tariffs define prices as a function of E and D, these are of primary interest here.

Empirically, we have found that the billing period load factor L is also a useful predictor of both average and marginal electricity prices [2, 14, 9]. The load factor is defined as the ratio of the average hourly demand to the peak hourly demand,

$$L = \frac{E}{N_h D}, \tag{12}$$

where N_h as the number of hours in the billing period. The value of L is bounded above by 1 and below by $1/N_h$. It is equal to one for a perfectly flat load, and is equal to $1/N_h$ in the extreme case where the load is zero in all hours except one. Different building activities or end-uses can be loosely characterized by their L values, with lower L corresponding to peakier loads.

Figures 3 through 5 show the distribution of monthly energy consumption E, demand D and load factor L. All figures use the same format. Data for the months of January and July are shown, with CBECS 1992 and 1995 data plotted separately. There are differences between the two survey years, which are likely due to either weather effects or sampling variation. Both the E and D distributions are multi-modal, with peaks at values that could be roughly defined as small (50kwa), medium (500kW) and large (5000kW). There is a notable shift of buildings from the small to medium category between 1992 and 1995. The shape of the E and D distribution reflects the actual size distribution of buildings—the load factor distribution is much smoother, with little variation between the survey years. There is a slight shift to higher load factors (flatter loads) for both January and July between 1992 and 1995.

3.1 Assignment of Customers to Tariffs

To develop a sample of bills from a sample of customers, each customer must be assigned to a tariff. We do so by first assigning a customer to a utility. The tariff rules then automatically determine which tariff is appropriate. The pairing of a particular building with a utility/tariff is referred to as an *account*, labeled by (b, u), where u is the utility index and b the building index. To enlarge the sample of accounts we assign each building to every utility in its region.

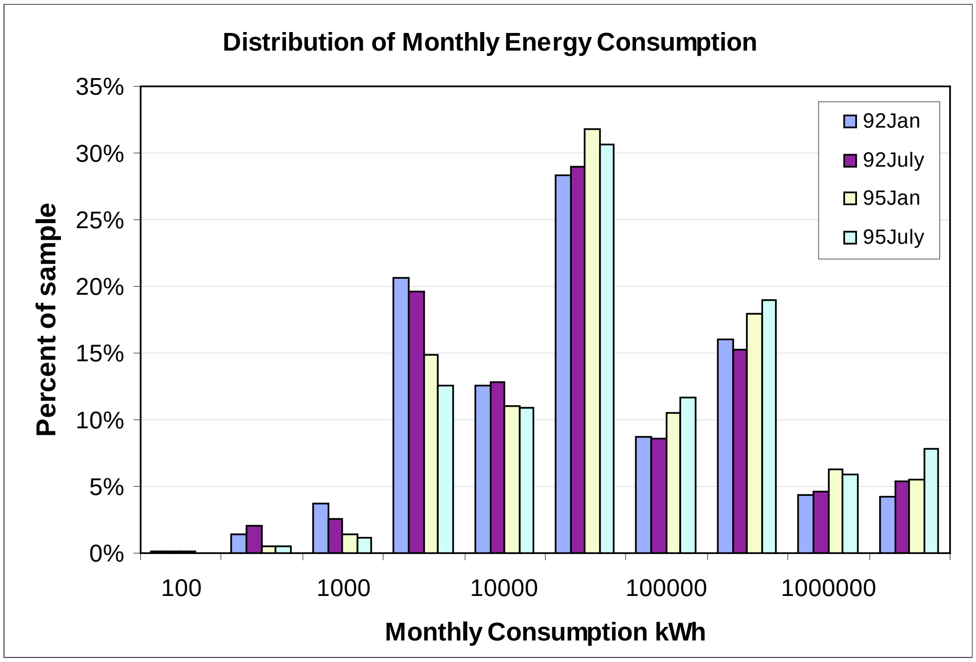

Figure 3: Distribution of monthly energy consumption, for January and July, for the CBECS data. The horizontal axis uses a logarithmic scale.

A weight $w(b, u)$ for the account is defined by multiplying the CBECS building weight by the utility weight defined in equation (9).

4 Calculation of Electricity Prices

In this section we present our calculation of regional weighted-average electricity prices. We present results based on the 1992 and 1995 survey data separately. We compute both annual average prices, and marginal prices as a function of the marginal load factor defined below. We also define the marginal *energy-only* and *demand-only* prices, and show how these can be combined with the MLF in a formula that allows us to associate a marginal price with a particular end-use.

Our notation is as follows: The billing period is one month indexed by m. In each billing period, energy consumption is E, demand is D and the total bill (expenditure) is B. Formally $B = f(E, D)$ where the function f is defined by the tariff rules. These numbers

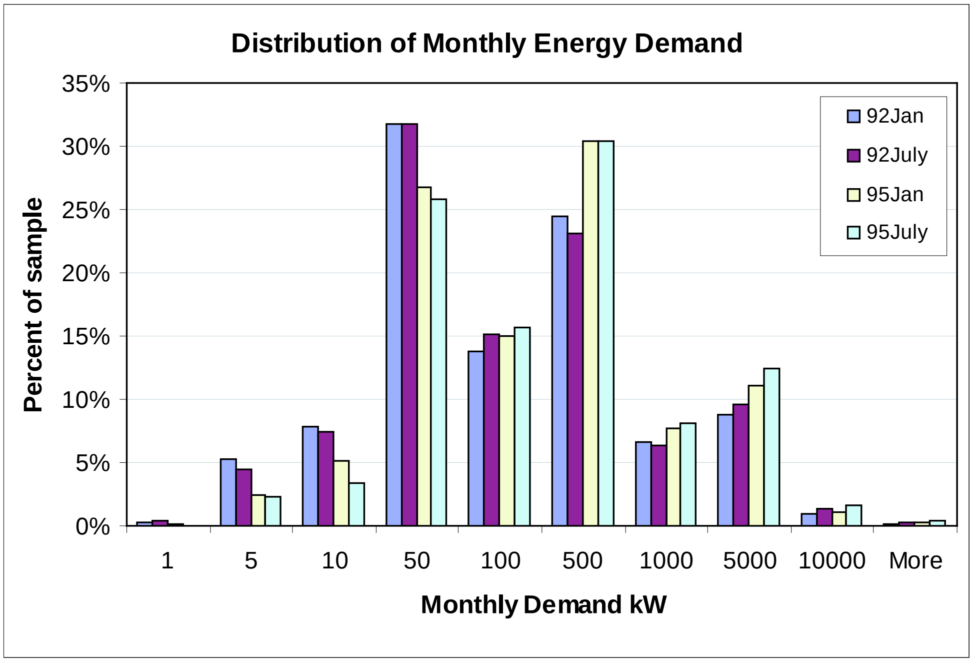

Figure 4: Distribution of monthly demand, for January and July, for the CBECS data. The horizontal axis uses a logarithmic scale.

also depend on the account indices (b, u).

4.1 Average Prices

The average electricity price p_{av} is defined as the total annual expenditure divided by the total annual energy consumption, computed by summing over calendar months. In equation form:

$$p_{av}(b, u) = \frac{\sum_m B(m, b, u)}{\sum_m E(m, b, u)} \tag{13}$$

A single value for a building is defined as the weighted sum over all accounts,

$$p_{av}(b) = \sum_u W(u) p_{av}(b, u), \tag{14}$$

where $W(u)$ is the utility weight. Values for summer and winter are computed by restricting the sums to the months May through August for summer, November through February for

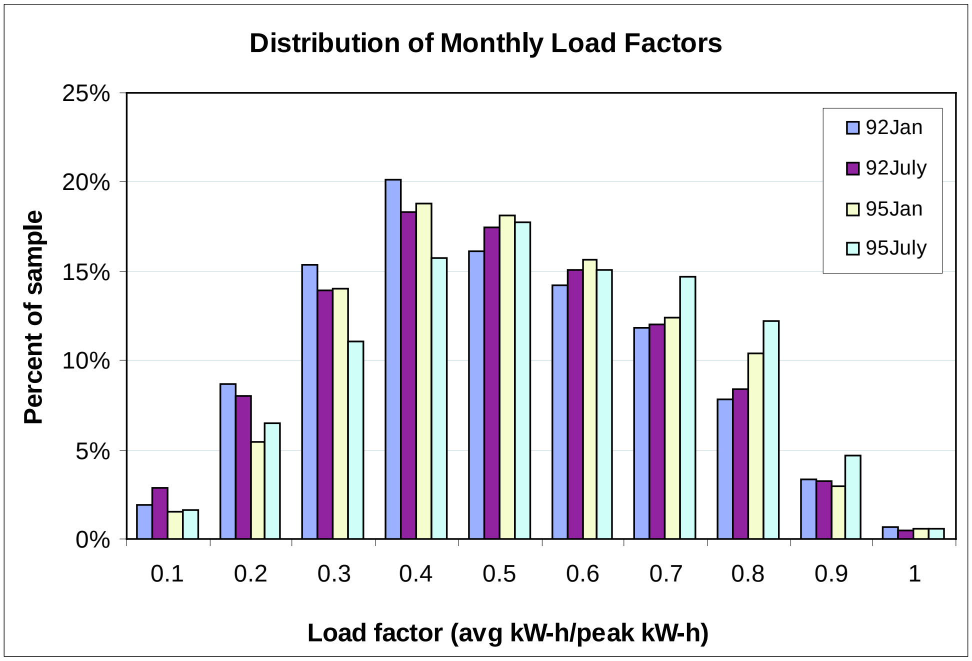

Figure 5: Distribution of monthly load factor, for January and July, for the CBECS data.

winter. Regional weighted sums are computed by multiplying each bill by the account weight $w(b, u)$ and summing over all buildings and utilities in the region.

$$P_{av}(R) = \sum_{b \in R} x(b) p_{av}(b) = \sum_{b \in R} \sum_{u} w(b, u) p_{av}(b, u). \tag{15}$$

Regional weighted averages are first calculated separately for the CBECS 1992 and 1995 data; we then take a simple average over the two sample years to define the regional value. National averages are defined by population-weighting the regional values. Prices are converted from 2004 to 2006 using the CPI for electricity [1].

Figures 6 through 8 illustrate how the average price varies with E, D and L. For these plots we use annual values for the energy consumption, peak demand and load factor. All figures use the same format, with the average price plotted on the vertical axis. For the demand and energy plots the horizontal axis is logarithmic. Each point corresponds to one account, with the 1992 and 1995 data plotted together. The highest priced regions are California (region 9.2) and the northeast and midwest (regions 1, 2 and 3), which are indicated separately on the plots. Overall, while there is a tendency toward lower prices

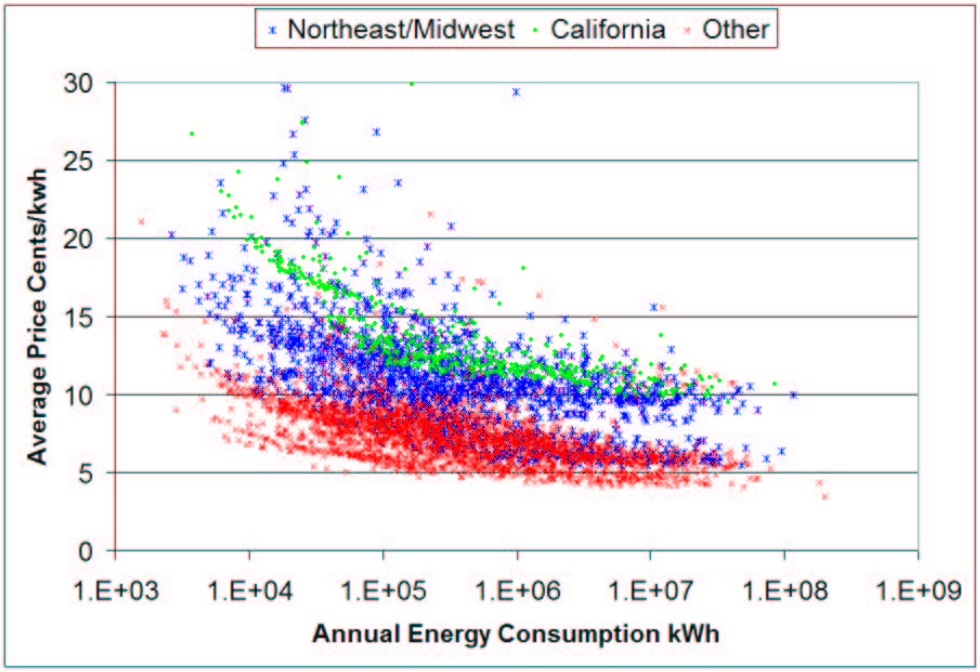

Figure 6: Tariff-based annual average electricity price *vs.* annual energy consumption; each point is one CBECS building. The horizontal axis is logarithmic.

for larger values of E and D, this trend is weak and at any given level of demand and consumption there is a large scatter in average price. Among the three variables, the load factor L shows the least scatter in prices, *i.e.* it is the best predictor of average price.

Tables 5 and 6 provide summary information by region. Table 5 shows the summer, winter and annual average price. In table 6 we calculate the fraction of all accounts, within each region, that fall into each of three price bins: less than 10¢/kWh; 10-15 ¢/kWh, and more than 15 ¢/kWh. The first column in table 6 gives the fraction of the total national accounts that are in each region.

4.2 Effective Marginal Prices

To compute marginal electricity prices we compare the bill B computed from the baseline quantities D and E to the bill B' calculated from the altered values D' and E'. We define

$$\Delta B = B - B', \ \Delta E = E - E', \text{ and } \Delta D = D - D'. \tag{16}$$

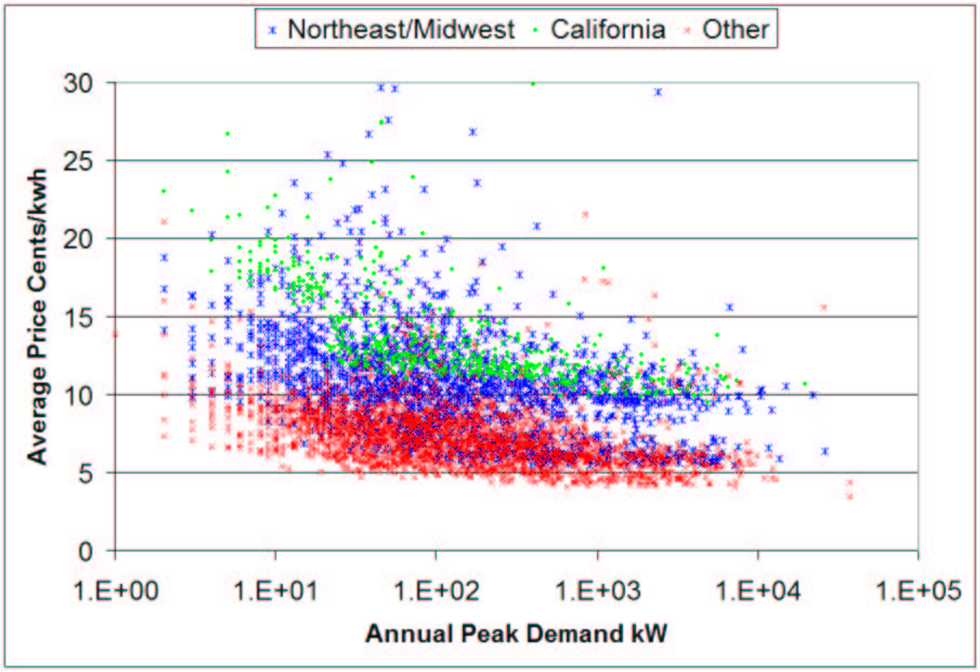

Figure 7: Tariff-based annual average electricity price *vs.* annual peak demand; each point is one CBECS building. The horizontal axis is logarithmic.

Region Name	Annual	Summer	Winter
New England	14.2	14.8	13.5
Mid-Atlantic	15.5	15.1	14.9
ENC	11.4	11.6	11.0
WNC	7.0	7.5	6.6
S. Atlantic	9.1	9.0	9.1
ESC	8.1	7.7	8.4
WSC	9.8	10.5	8.9
N. Mountain	6.0	6.2	6.0
S. Mountain	10.6	10.6	10.5
N. Pacific	7.2	7.3	7.1
California	17.2	18.3	16.1
National	11.4	11.8	11.0

Table 5: Tariff-based average seasonal and annual electricity prices by region in ¢/kWh.

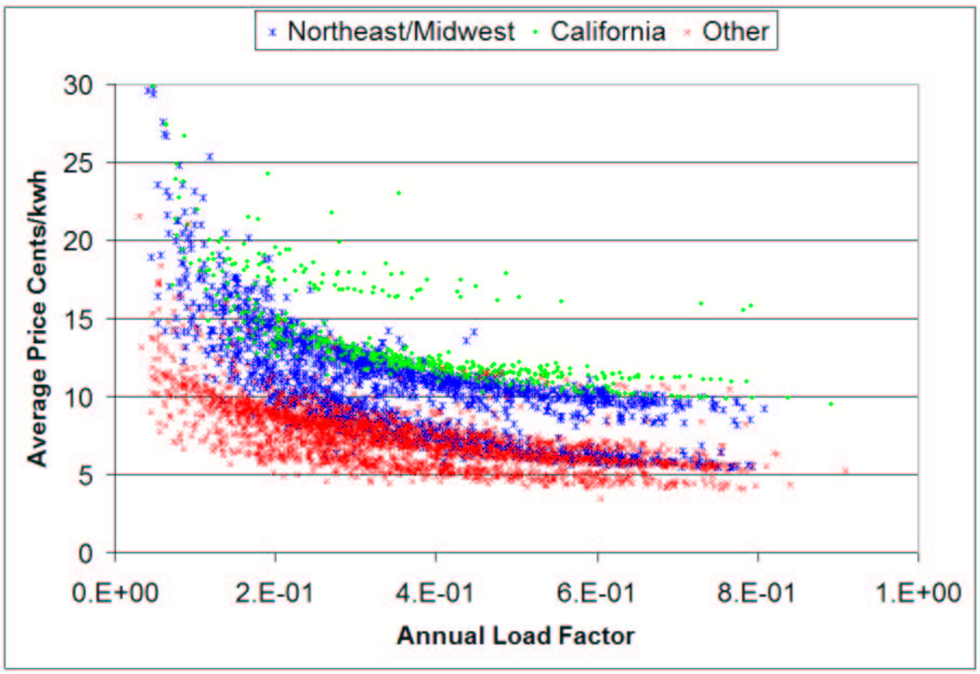

Figure 8: Tariff-based annual average electricity price *vs.* annual load factor; each point is one CBECS building.

Region	All accounts	< 10 ¢/kWh	10-15 ¢/kWh	> 15 ¢/kWh
New England	4.1 %	19 %	70 %	12 %
Mid-Atlantic	14.7 %	28 %	39 %	32 %
ENC	15.2 %	63 %	30 %	8 %
WNC	7.8 %	99 %	1 %	0 %
South Atlantic	14.7 %	91 %	8 %	1 %
ESC	9.3 %	96 %	3 %	2 %
WSC	17.4 %	96 %	4 %	0 %
N. Mountain	0.8 %	100 %	0 %	0 %
S. Mountain	5.5 %	69 %	27 %	5 %
N. Pacific	1.7 %	98 %	2 %	0 %
California	8.8 %	14 %	61 %	25 %
National	100 %	70 %	25 %	10 %

Table 6: Percent of accounts in each price bin. The first column shows the percent of all accounts in each region.

Here ΔD is the load decrement during the hour of the customer's peak demand, and ΔE is the total energy decrement, for a given billing period. In general the differences ΔE and ΔD are independent variables, but under a given energy efficiency measure there will be some functional relationship between the two. The effective marginal price Π is defined as the ratio

$$\Pi = \Delta B/\Delta E \tag{17}$$

This definition is completely general and does not depend on the structure of the tariff. It has little relation in practice to the value of the energy charge in the highest rate block on a tariff. If the cost benefits associated with an efficiency measure are calculated by multiplying the estimated energy savings by a price for energy, then Π is the correct price to use. Any under- or over-estimate of benefits that results from using a different price is directly related to the difference between that price and the price Π.

4.3 Marginal Energy and Demand Prices

The effective marginal price defined above glosses over the complications of tariff documents and goes straight to the number that is of interest in practical applications. With a little manipulation of equation (17) we can derive two additional useful numbers: the *energy-only*

	Π_E in ¢/kWh			Π_D in \$/kW		
Region Name	Annual	Summer	Winter	Annual	Summer	Winter
New England	9.2	9.3	9.0	11.6	13.3	10.4
Mid-Atlantic	9.5	9.8	9.2	12.8	13.9	11.9
ENC	5.8	5.9	5.7	11.2	11.8	10.7
WNC	5.0	5.3	4.7	4.8	5.5	4.3
S. Atlantic	6.3	6.3	6.3	7.0	7.3	6.9
ESC	5.5	5.3	5.6	6.3	6.7	6.1
WSC	7.5	8.2	6.6	5.0	5.7	4.5
N. Mountain	4.8	4.9	4.7	3.8	3.8	3.8
S. Mountain	7.1	7.1	7.2	8.1	8.3	8.0
N. Pacific	5.7	5.7	5.7	2.6	2.6	2.6
California	12.5	12.7	12.2	7.0	9.6	4.6
National	7.6	7.8	7.4	8.1	9.0	7.5

Table 7: Tariff-based marginal energy-only and demand-only prices by region.

marginal price Π_E and the *demand-only* marginal price Π_D. Formally we define

$$\Pi_E = \frac{\Delta B}{\Delta E}\Big|_{\Delta D = 0}, \tag{18}$$

and

$$\Pi_D = \frac{\Delta B}{\Delta D}\Big|_{\Delta E = 0} \tag{19}$$

The energy-only price is defined by calculating the change in the bill when the demand is held fixed, and similarly for the demand-only price. (For TOU tariffs, these numbers are calculated assuming that the same proportional decrease in energy or demand occurs in all TOU periods.) The demand-only marginal price Π_D is not the same as the demand charge. It is defined empirically, and combines the impact of ordinary demand charges and block-by-demand tariffs or whatever other structure may occur in the tariff. We note that, given the complexity of some tariff structures, it is not possible to define energy- or demand-only average prices; these concepts only make sense at the margin.

Table 7 gives regional values for the energy-only and demand-only marginal prices, both seasonal and annual values. The regional weighted averages are calculated in the same way as for average prices. Seasonal differences in Π_E and Π_D are generally not large, except for Π_D in the northeast and California.

It is straightforward to define Π in terms of the demand- and energy-only components. For sufficiently small, but otherwise arbitrary, ΔE and ΔD we have the identity

$$\Delta B = \Pi_D \Delta D + \Pi_E \Delta E, \tag{20}$$

which leads directly to

$$\Pi = \Pi_D(\Delta D/\Delta E) + \Pi_E, \quad ; \Delta E > 0. \tag{21}$$

The case $\Delta E = 0$ corresponds to a change in energy demand with no change in energy consumption, an example of pure load-shifting, which we won't consider here. Equation (21) shows that the ratio $\Delta D/\Delta E$ is a determinant of the marginal price, as it defines the relative weighting of Π_D and Π_E. We account for this dependence by introducing the *marginal load factor* λ, which is defined as the the ratio of the average hourly energy decrement to the demand decrement:

$$\lambda = \frac{\Delta E}{N_h \Delta D}, \tag{22}$$

where N_h is the number of hours in the billing period (here we set $N_h = 8760/12 = 730$). The marginal load factor satisfies $0 \leq \lambda \leq 1$, and is larger for decrements to flat loads and smaller for peaking loads. Combining equations (21) and (22), the effective marginal price can be written as

$$\Pi = \Pi_E + \frac{\tilde{\Pi}_D}{\lambda}, \quad \lambda > 0 \tag{23}$$

with

$$\tilde{\Pi}_D = \Pi_D/N_h. \tag{24}$$

The rescaled demand-only price $\tilde{\Pi}_D$ now has the same units as Π_E (¢per kWh). The factor λ^{-1} determines the weight of the demand contribution relative to the energy contribution. Equation (23) provides a simple way to estimate the marginal price appropriate to a specific energy efficiency measure, assuming the appropriate marginal load factor can be determined. Note that the MLF depends both on the shape of the load decrement and its degree of coincidence with the building peak load.

The behavior of Π as a function of the marginal load factor λ is shown in figure 9 by region. For clarity, the North Mountain, East South Central and West North Central regions are not plotted. The curves for these regions are very close to the West South Central curve. The limit $\lambda = 1$ corresponds to a perfectly flat load decrement. As noted above, equation (23) is not valid in the limit $\lambda = 0$. In table 8, for each region, we give specific values of the effective marginal price for high ($\lambda = 0.75$), medium ($\lambda = 0.5$) and low ($\lambda = 0.25$) values of the marginal load factor.

Region Name	$\lambda = 0.75$	$\lambda = 0.50$	$\lambda = 0.25$
New England	11.3	12.4	15.5
Mid-Atlantic	11.8	13.0	16.5
ENC	7.8	8.9	11.9
WNC	5.9	6.3	7.6
S. Atlantic	7.6	8.2	10.1
ESC	6.6	7.2	8.9
WSC	8.4	8.8	10.2
N. Mountain	5.5	5.8	6.9
S. Mountain	8.6	9.4	11.6
N. Pacific	6.2	6.4	7.1
California	13.8	14.5	16.4
National	9.1	9.8	12.0

Table 8: Tariff-based effective marginal price (¢/kWh) as a function of marginal load factor.

The energy- and demand-only marginal prices are also functions of the baseline E and D values for the customer, but for the most part they are weak functions of these quantities. To illustrate, figure 10 shows Π calculated with $\lambda = 0.5$ as a function of the customer annual peak demand. Plots of Π *vs.* E and the annual load factor look very similar. There is less vertical scatter in Π than in p_{av}, but overall variance in the marginal price is dominated by regional variation and the value of λ that is used.

Figure 11 illustrates in a general way the difference between the marginal and average prices. It shows the probability that the marginal price will exceed the average price as a function of the marginal load factor λ. The idea here is to try to get a sense of the likelihood that an efficiency measure would be over- or under-valued, and by how much, when an average price is substituted for the correct marginal price. This clearly depends on the measure under consideration, which is here represented by the marginal load factor. The figure shows both the probability that the marginal price will exceed the average price (bars), and the sample mean value of the difference $\Pi - p_{av}$ (points) as a function of λ, for the country as a whole. The two are roughly equal near $\lambda = 0.3$. For higher load factors the mean marginal price decreases below p_{av}, but the decrease is slow. The probability that Π will actually be above p_{av} remains greater than 10% until you reach marginal load factors of 0.7 or more. For low load factors (peakier loads) $\lambda < 0.3$, the marginal price is very likely to be larger than p_{av} by a rapidly increasing amount. These numbers represent averages for the entire commercial customer population as represented by CBECS 1992 and 1995. For a given tariff, or more specific customer sample, the results could look quite different. The

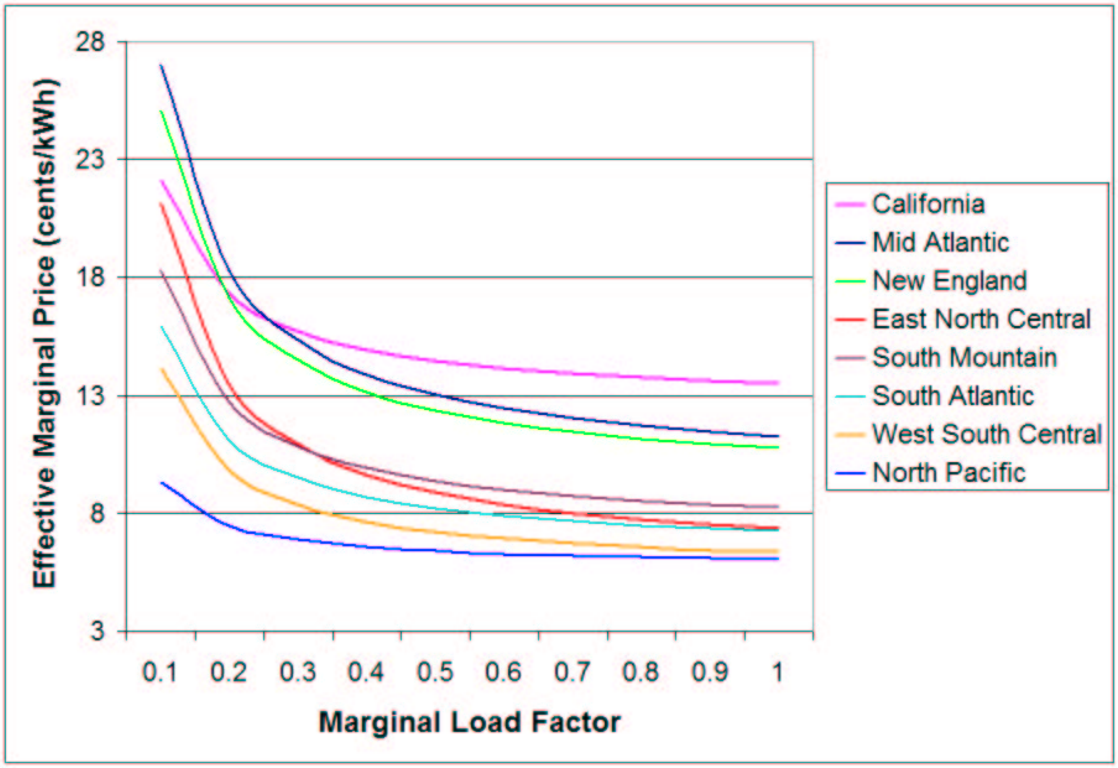

Figure 9: Effective marginal price as a function of marginal load factor by region. Note that the MLF decreases going right on the horizontal axis, corresponding to peakier loads.

curves presented in figure 9 can be used to determine the marginal load factor at which Π equals p_{av} by region.

5 Summary and Conclusions

This paper presents the results of a survey and analysis of electricity tariffs and marginal electricity prices for commercial buildings. The tariff data come from a survey of 90 utilities and 250 tariffs for non-residential customers collected in 2004. The customer data are derived from detailed utility billing data collected during the CBECS 1992 and 1995 surveys. This work is in part a result of the Tariff Analysis Project undertaken at LBNL [2] in which a set of database and analytical tools are being developed to facilitate the use of real tariff data in policy analysis.

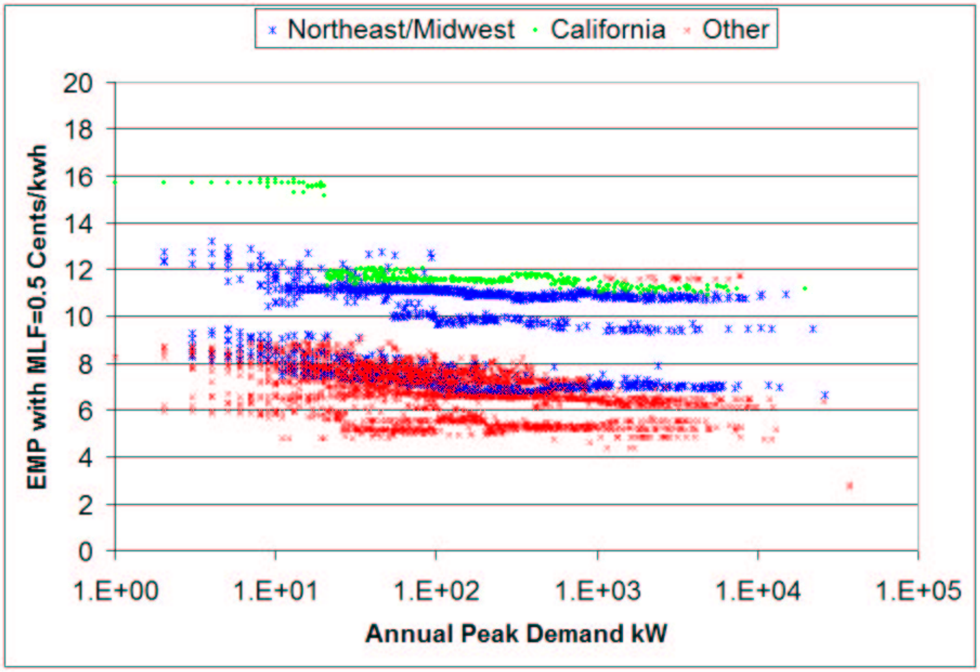

Figure 10: Effective marginal electricity price as a function of annual peak demand; each point is one CBECS building.

A goal of this analysis is to provide useful summary data on the marginal electricity prices commercial customers actually see in the real world, and to determine the extent to which using actual tariffs–rather than average prices derived from bill surveys or revenue data–changes the valuation of diverse energy efficiency measures. Another goal is to provide insight into which factors are most important in determining marginal prices under different circumstances.

The most important conclusions emerging from this analysis are: (1) customer prices depend as much on the customer load characteristics as they do on the tariff itself; (2) load factors, both for the baseline and at the margin, are more strongly determinant of prices than customer size; (3) regional differences in prices are extremely important, and can be much larger than is indicated by EIA Form 861 data; (4) demand impacts are very important at the margin, but may be obscured by tariff structures such as block-by-demand.

Analytically, we have developed a new, empirically-based definition of several marginal prices: the effective marginal price, and energy-only and demand-only prices. These are conceptually straightforward and can be calculated for any customer sample of interest,

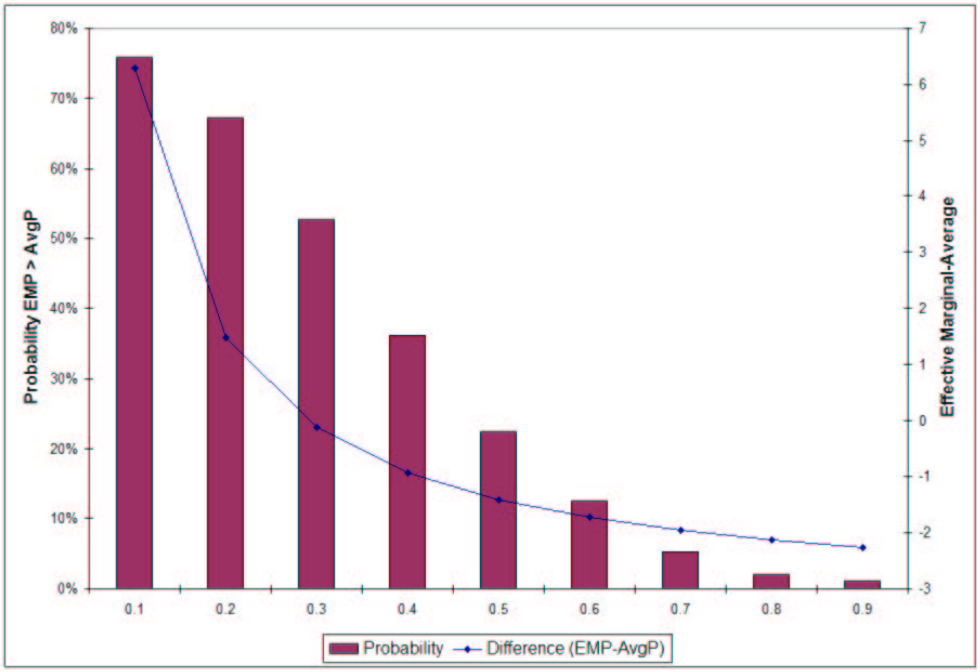

Figure 11: Probability that the marginal price will exceed the average price (bars, left-hand scale), and the sample mean value of the difference (line, right-hand scale), as a function of marginal load factor.

greatly facilitating the comparison of prices across different types of customers, different regions *etc.* We have also developed a simple formula that expresses the dependence of the effective marginal price on the marginal load factor. The latter is a variable that can be used to characterize the load impacts of a particular end-use or efficiency measure. This formula cleanly separates the price effects of the utility's tariff rules from those due to customer load characteristics, and allows a suite of efficiency measures to be priced without requiring detailed information on the load impacts of each measure.

We have also provided quantitative estimates of all these prices for eleven regions within the continental U.S. This data can be used to provide quick but accurate estimation of the real marginal price impacts of different types of efficiency measures for commercial customers. The methodology developed here can be adapted to any particular customer or utility subsample that may be of interest. Using the tools developed for the TAP project, large amounts of data can be managed easily, and the calculations can be done quickly, irrespective of how complicated the tariff formulae may be.

In the future, we hope to make the TAP tools and data available to the wider energy research and planning community, so as to facilitate the use of accurate pricing and improve the cost-effectiveness of energy policy.

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A Processing of Commercial Building Customer Load Data

This appendix describes the data processing steps used to convert the available raw data to the form needed for the tariff bill calculations. The EIA Commercial Building Energy Consumption Surveys (CBECS) monthly billing data is used to develop energy consumption and demand values for twelve calendar months, which are used to calculate bills for non-TOU tariffs. To calculate bills for TOU tariffs, energy demand and consumption are required for each month and each TOU period. As described below, we have developed a method to calculate the TOU period values from the monthly values using a statistical model. The model parameters are calculated for a given definition of TOU period hours using hourly whole-building simulation data for a sub-set of the commercial buildings in the CBECS 1995 sample. The model is then applied to the CBECS monthly bill data to estimate TOU inputs for these records.

A.1 CBECS sample of commercial buildings

The Commercial Building Energy Consumption Survey contains comprehensive information for a statistically representative sample of roughly 6000 buildings. Buildings are assigned to census divisions and climate zones, and each record is given a weight that reflects the number of similar buildings that exist in the same region. Monthly electricity bill data is available for the 1992 and 1995 surveys, which form the basis of our present analysis. The data consist of electricity consumption, demand and expenditure values for a subset of the full building set, for anywhere from 1 to 16 billing periods which cover the survey year.

For this analysis, we require each building to have both demand and energy values for twelve calendar months. Screening out building records that have insufficient or poor quality data results in a sub-sample containing about 45% of the buildings in the full sample. Any building with demand and energy data for at least ten distinct calendar months is included; if necessary, we use linear interpolation to estimate the values for missing months. The monthly demand values are used to assign customers to a particular tariff as described above.

A.2 Preparation of the CBECS data

The quality checks used on the data are summarized below.

1. All monthly records that are missing either demand or energy values are dropped from the data set.

2. Any records with a billing period of more than 45 days are eliminated from the data set.

3. Two checks are used to ensure consistency between the energy consumption and demand data.

   (a) We verify the physical constraint that the monthly load factor (ratio of average hourly load to demand) is bounded by one; any records that do not satisfy this constraint are dropped. This is equivalent to imposing a lower bound on the demand.

   (b) We impose an upper bound on the demand defined by a factor β times the average daily energy consumption for the billing period. A value for β of 1.2 was determined empirically to be sufficient to screen for outliers. Any records with demand greater than this upper bound is discarded.

4. Building accounts which do not have both consumption and demand data for at least ten distinct calendar months are dropped. The account is also dropped if two or more consecutive months are missing.

5. Accounts are screened for situations where a customer's energy use pattern varies dramatically by season. Large seasonal variation can lead to unrealistic results for prices, so this type of account is dropped from the analysis. In reality, these cases are handled by special tariff rules which are not currently modeled. The screening process uses ratios of the minimum D_{min}, maximum D_{max} and average demand D_{avg} over all non-zero values for a given account. Empirically we find that requiring $D_{max}/D_{avg} \leq 3$ and $D_{max}/D_{min} \leq 8$ ensures that the variation in energy use across the year is within reasonable bounds. There is no dependence of the calculation results on the precise values used for the screening parameters.

The raw CBECS data is for billing periods which may be non-uniform, which must be interpolated onto regular calendar months for this analysis. For the energy consumption data, within each billing period the average daily energy consumption is computed, then the appropriate sums are taken for the calendar months. This is equivalent to linear interpolation. For the demand data a number of different methods were tested, including spline interpolation, but it was found that a relatively simple shift technique is sufficient. Here the demand value for a given billing period is simply shifted to the nearest calendar month. After the calendar month values are computed, we re-confirm that the monthly load factor is less than or equal to one.

Once the quality control steps are complete, there may be accounts which lack demand data for one or two calendar months. In these cases, if the missing months are not consecutive, we use linear interpolation to estimate the missing values. While more sophisticated methods are available, given the relatively large amount of data we use, and the many steps of processing taken to arrive at final prices, inaccuracies introduced by this particular approximation should be negligible.

A.3 Creation of TOU monthly bill inputs

To calculate bills for TOU tariffs, it isn't sufficient to have the monthly energy consumption and demand — we need these values for each TOU period separately. To obtain them we construct a model that estimates the TOU period values from the known monthly energy and consumption and demand. This relationship depends on the definition of the TOU periods, so we develop a separate set of model parameters for each TOU tariff.

Conceptually, the approach is straightforward if one has hourly data for a sufficiently large set of sample buildings. Here we use full-year simulation data for a set of 1033 buildings drawn from CBECS 1995, developed originally for use in the DOE CUAC rule-making analysis [14]. The idea is to calculate the monthly and TOU period values directly for the set of sample buildings, and then use this data to estimate a linear relationship between the monthly and TOU values.

For a given tariff the procedure is as follows: Assume a sample of N buildings indexed by b with hourly loads $l(i, b)$, where $i = 1, \ldots 8760$ indicates the hour. To date, TOU tariffs use a maximum of 3 periods, which we refer to as off-peak, on-peak and shoulder. These are indexed by by $\tau = 1, 2, 3$. The periods are specified using an hourly mask $X(i, \tau)$. The mask $X(i, \tau)$ equals one if hour i is in period τ, and zero otherwise. For building b we define the energy consumption and demand for month m and period τ, to be $e(b, m, \tau)$ and $d(b, m, \tau)$ respectively. By definition

$$e(b, m, \tau) = \sum_{i \in \text{month } m} X(i, \tau) l(i, b) \tag{25}$$

and

$$d(b, m, \tau) = \max_{i \in \text{month } m} X(i, \tau) l(i, b) \tag{26}$$

We define $E(b, m)$ to be the total energy consumption, and $D(b, m)$ the peak demand for month m. It follows that

$$E(b, m) = \sum_{\tau} e(b, m, \tau), \tag{27}$$

and

$$D(b, m) = \max_{\tau} \{d(b, m, \tau)\}. \tag{28}$$

Our hypothesis is that for a given definition of the TOU periods, the ratios $e(b,m,\tau)/E(b,m)$ and $d(b,m,\tau)/D(b,m)$ can be characterized by a statistical distribution with mean and width calculated from the data. The distribution means for the energy and demand are

$$\mu_E(\tau) \equiv \frac{1}{12N} \sum_b \sum_m \frac{e(b,m,\tau)}{E(b,m)}, \tag{29}$$

and

$$\mu_D(\tau) \equiv \frac{1}{12N} \sum_b \sum_m \frac{d(b,m,\tau)}{D(b,m)}, \tag{30}$$

The distribution widths are defined using the average absolute deviation from the mean:

$$W_E(\tau) \equiv \frac{1}{12N} \sum_b \sum_m |\mu_E(\tau) - e(b,m,\tau)/E(b,m)|, \tag{31}$$

and

$$W_D(\tau) \equiv \frac{1}{12N} \sum_b \sum_m |\mu_D(\tau) - d(b,m,\tau,u)/D(b,m)|. \tag{32}$$

For simplicity, we assume that the shape of the distribution is flat over the interval $[\mu_E - W_E, \mu_E + W_E]$ for the energy and similarly for the demand. For the demand, the maximum upper bound on the interval is equal to one. More elaborate models may be useful in some applications, but as we are ultimately intersted in calculating averages over many buildings and many utility tariffs, this simple model is sufficient to capture the essential features of the data.

The model parameters should be independent of the building sample used to derive them, assuming that the sample is large enough. The sample used here includes 1033 buildings of all types and sizes, and is sufficient to cover the range of energy use characteristics in the CBECS sample. Once the model parameters are known, the model can be applied to any data set. In applying the model we also enforce the conditions expressed in equations (27) and (28), and ensure that the load factors calculated for each TOU period are less than or equal to one.

For buildings that have been assigned to TOU tariffs, we use the model for that tariff to estimate the appropriate TOU period values. The number of buildings that may be assigned to any particular tariff ranges from roughly 10 to 100, which is large enough to smooth out fluctuations in the statistical behavior of the model. This is illustrated in Figure 12 for a TOU tariff used in California. In this example, the building data come from the hourly simulation data set, so we can compare prices calculated with the actual TOU period data to those calculated with TOU period data generated by the model. All of the buildings in

California on this tariff are shown on the plot (in this case there are 20). The figure shows the average price for each building for the summer months, winter months and annually, as well as regression lines fit to the summer and winter data. To 3 significant figures, the regression coefficient is 1.00. There is some scatter in the data, particularly at the high and low ends, which is likely due to the fact that a flat distribution produces slightly more high and low values than would occur in reality. But over the building sample these fluctuations average out.

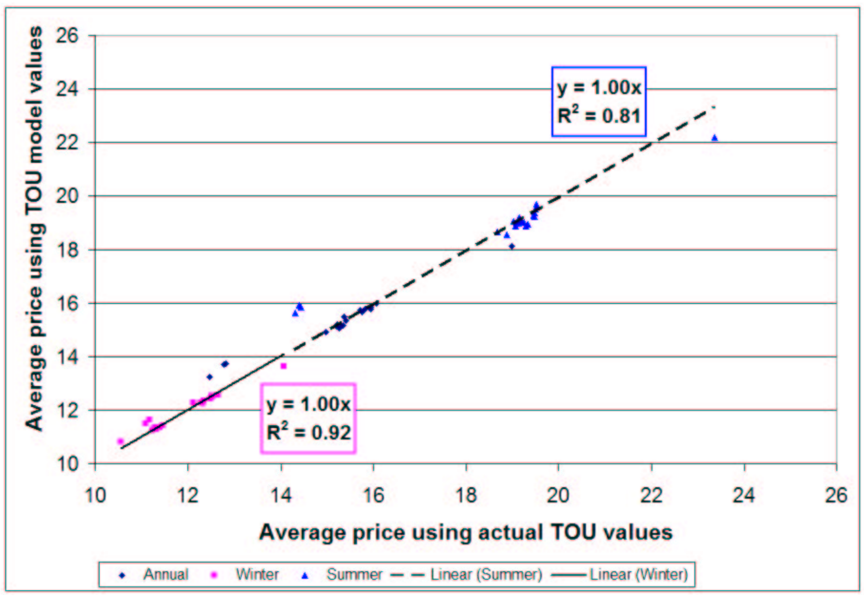

Figure 12: Scatter plot of average prices for a single TOU tariff, calculated using the actual TOU period values (horizontal) and the TOU period energy and demand generated by the model (vertical).

B List of Sample Utilities

Company Name	State	Region	Ownership	Size	EIA Code
Boston Edison Co	MA	1	Private	Medium	1998
Central Vermont Pub Serv Corp	VT	1	Private	Small	3292
Connecticut Light & Power Co	CT	1	Private	Large	4176
Energy Atlantic LLC	ME	1	Private	Medium	6223
Norwich City of	CT	1	Public	Small	13831
Public Service Co of NH	NH	1	Private	Medium	15472
Central Electric Coop Inc	PA	2	Public	Small	40224
Consolidated Edison Co-NY Inc	NY	2	Private	Large	4226
Duquesne Light Co	PA	2	Private	Medium	5487
Ephrata Borough of	PA	2	Public	Small	5935
Freeport Village of Inc	NY	2	Public	Small	6775
Jamestown Board of Public Util	NY	2	Public	Small	9645
Long Island Power Authority	NY	2	Government	Large	11171
Niagara Mohawk Power Corp	NY	2	Private	Large	13573
PECO Energy Co	PA	2	Private	Large	14940
Public Service Electric & Gas Co	NJ	2	Private	Large	15477
Rockland Electric Co	NJ	2	Private	Small	16213
West Penn Power Co	PA	2	Private	Medium	20387
Cleveland City of	OH	3	Public	Small	3762
Commonwealth Edison Co	IL	3	Private	Large	4110
Consumers Energy Co	MI	3	Private	Large	4254
Dayton Power & Light Co	OH	3	Private	Medium	4922
Great Lakes Energy Coop	MI	3	Public	Small	38084
Illinois Power Co	IL	3	Private	Medium	9208
Northern Indiana Pub Serv Co	IN	3	Private	Medium	13756
Ohio Edison Co	OH	3	Private	Large	13998
Springfield City of	IL	3	Public	Small	17828
Wisconsin Public Service Corp	WI	3	Private	Medium	20860
Ames City of	IA	4	Public	Small	554
Anoka Electric Coop	MN	4	Public	Small	689
Kansas City Power & Light	KS	4	Private	Medium	10005
Lincoln Electric System	NE	4	Public	Small	11018
MidAmerican Energy Co	IA	4	Private	Medium	12341
Northern States Power Co	MN	4	Private	Large	13781
Springfield City of	MO	4	Public	Small	17833
Union Electric Co	MO	4	Private	Large	19436
Appalachian Power Co	VA	5	Private	Large	733
Baltimore Gas & Electric Co	MD	5	Private	Large	1167
Carolina Power & Light Co	NC	5	Private	Large	3046
Clay Electric Coop Inc	FL	5	Public	Small	3757
Delmarva Power & Light Co	DE	5	Private	Medium	5027
Duke Energy Corp	NC	5	Private	Large	5416

Company Name	State	Region	Ownership	Size	EIA Code
Fayetteville Public Works Comm	NC	5	Public	Small	6235
Florida Power & Light Co	FL	5	Private	Large	6452
Florida Public Utilities Co	FL	5	Private	Small	6457
Georgia Power Co	GA	5	Private	Large	7140
Jackson Electric Member Corp	GA	5	Public	Small	9601
Marietta City of	GA	5	Public	Small	11646
Monongahela Power Co	WV	5	Private	Medium	12796
Orlando Utilities Comm	FL	5	Public	Small	14610
South Carolina PSA (Santee Cooper)	SC	5	Government	Small	17543
Southern Maryland Elec Coop Inc	MD	5	Public	Small	17637
Tampa Electric Co	FL	5	Private	Medium	18454
Virginia Electric & Power Co	VA	5	Private	Large	19876
Alabama Power Co	AL	6	Private	Large	195
Coast Electric Power Assn	MS	6	Public	Small	3841
Cumberland Elec Member Corp	TN	6	Public	Small	4624
Huntsville City of	AL	6	Public	Small	9094
Kentucky Utilities Co	KY	6	Private	Medium	10171
Memphis City of	TN	6	Public	Medium	12293
Owen Electric Coop Inc	KY	6	Public	Small	14251
Beauregard Electric Coop Inc	LA	7	Public	Small	1458
Entergy Arkansas Inc	AR	7	Private	Medium	814
Entergy Louisiana Inc	LA	7	Private	Medium	11241
Magic Valley Electric Coop Inc	TX	7	Public	Small	11501
Oklahoma Electric Coop Inc	OK	7	Public	Small	14062
Oklahoma Gas & Electric Co	OK	7	Private	Medium	14063
Paragould Light & Water Comm	AR	7	Public	Small	14446
Reliant Energy HL&P	TX	7	Private	Large	8901
San Antonio Public Service Bd	TX	7	Public	Medium	16604
Flathead Electric Coop Inc	MT	8.1	Public	Small	6395
Idaho Power Co	ID	8.1	Private	Medium	9191
Arizona Public Service Co	AZ	8.2	Private	Large	803
Farmington City of	NM	8.2	Public	Small	6204
Mountain View Elec Assn Inc	CO	8.2	Public	Small	13058
Murray City of	UT	8.2	Public	Small	13137
Nevada Power Co	NV	8.2	Private	Medium	13407
Public Service Co of Colorado	CO	8.2	Private	Large	15466
United Power Inc	CO	8.2	Public	Small	19499
Central Electric Coop Inc	OR	9.1	Public	Small	3240
PacifiCorp	OR	9.1	Private	Large	14354
Seattle City of	WA	9.1	Public	Medium	16868
Anaheim City of	CA	9.2	Public	Small	590
Pacific Gas & Electric Co	CA	9.2	Private	Large	14328
Redding City of	CA	9.2	Public	Small	15783
Sacramento Municipal Util Dist	CA	9.2	Public	Medium	16534
San Diego Gas & Electric Co	CA	9.2	Private	Large	16609
Southern California Edison Co	CA	9.2	Private	Large	17609